

Beyond Data, towards Decisions: The Mediating Role of Information Use in Inventory Replenishment Effectiveness

Ahmad Amru Mohamad Zaid^{1*}, Nur Athirah Abd Rahim²

¹School of Computing and Artificial Intelligence, Malaysia University of Science and Technology, 47810 Petaling Jaya, Selangor, Malaysia, ²School of Business Management, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia
Corresponding Author Email: ahmadamru@must.edu.my

DOI Link: <http://dx.doi.org/10.6007/IJARBSS/v16-i10/29164>

Published Date: 25 October 2026

Abstract

This study examines the relationships among information quality (IQ), analytical capability (AC), decision information use (DIU), and perceived replenishment decision effectiveness (RDE) among small and medium-sized enterprises (SMEs) in Selangor, Malaysia. Drawing on organisational information-processing theory, the study distinguishes the quality of decision inputs and the capability to interpret them from their actual use in inventory replenishment. A survey of 360 SME respondents was conducted using purposive sampling in October 2026. The four constructs were represented by four five-point items each, and the reported analysis used composite-score regression and 2,500-resample percentile bootstrapping to examine direct and indirect associations. IQ and AC were positively associated with DIU ($\beta = 0.430$ and $\beta = 0.213$, respectively), while DIU was associated with RDE after accounting for both predictors ($\beta = 0.255$). The specific indirect associations were 0.110 and 0.054, with reported confidence intervals excluding zero. The mediator and outcome models explained 24.9% and 16.5% of the variation in their respective outcomes. The findings highlight decision information use as an empirically specified link between organisational information resources and perceived replenishment effectiveness, while remaining associational rather than causal.

Keywords: Information Quality, Analytical Capability, Decision Information Use, Inventory Replenishment, Organisational Information-Processing Theory

Introduction

Inventory replenishment requires small and medium-sized enterprises (SMEs) to determine order quantities, timing and supplier choices despite uncertainty in customer demand, recorded stock positions and replenishment lead times. These decisions can be affected by discrepancies between physical stock and inventory records (DeHoratius & Raman, 2008), while forecasting practices, lead times and information arrangements influence variability across supply chains (Chen et al., 2000). Nevertheless, possessing inventory data is not equivalent to using it appropriately when an order is placed. Information quality encompasses

not only accuracy but also relevance, completeness, accessibility and fitness for decision-making purposes (Wang & Strong, 1996). An important question is therefore how decision-relevant information and the capability to interpret it are associated with the actual use of information in replenishment choices and, ultimately, with perceived decision effectiveness.

Existing research offers important but incomplete explanations of this decision-level relationship. Cao et al. (2015) link business analytics, information-processing capability and organisational decision-making effectiveness; Chen et al. (2022) examine analytics capability in strategic decision-making under disruption; and Abdellatif et al. (2024) investigate decision speed and comprehensiveness as mediating facets of decision quality. Lem (2024) considers analytics strategy and internal information quality, whereas Raj et al. (2025) synthesise connections between analytics, broader supply-chain capabilities and operational performance. These contributions predominantly address organisational capabilities, strategic decisions or aggregate performance outcomes rather than the reported use of specific information when selecting replenishment quantities and timing. Closer to the operational decision process, Jonsson and Myrelid (2016) distinguish information availability and quality from actual supply-chain information utilisation. However, that conceptual precedent does not itself establish the simultaneous relationships among perceived information quality, analytical capability, replenishment-specific information use and perceived decision effectiveness in the four-construct model tested here. The gap is thus not the absence of information-utilisation research, but insufficient decision-level specification of how input quality and interpretive capability relate to information use and effectiveness within the same replenishment model.

Organisational Information Processing Theory (OIPT) provides a rationale for examining these distinctions together: organisations must align information-processing arrangements with the uncertainty of their tasks (Galbraith, 1974). Applied to inventory replenishment, information quality (IQ) represents the fitness of available decision inputs; analytical capability (AC) represents the perceived capacity to interpret and compare those inputs; decision information use (DIU) represents their reported incorporation into ordering judgments; and replenishment decision effectiveness (RDE) represents respondents' assessments of decision appropriateness and timeliness. Examining these constructs jointly avoids treating data quality, analytical competence and use as interchangeable indicators of digital sophistication. It also permits estimation of whether DIU carries statistical indirect associations between IQ or AC and RDE while the corresponding direct relationships remain in the model. The theoretical contribution is consequently a more operationally specific, behaviourally articulated application of OIPT, rather than a claim to introduce information utilisation or to establish a causal mediation mechanism (Cao et al., 2015; Jonsson & Myrelid, 2016; Maxwell & Cole, 2007).

Selangor SMEs offer a useful empirical setting in which to examine this decision-process distinction because replenishment decisions must be made within the informational, analytical and organisational resources accessible to respondents. The study does not assume that Malaysian SMEs share a single resource profile or differ categorically from enterprises elsewhere. Rather, it evaluates whether theoretically distinct information-processing components can be identified in a specific SME operating setting without presupposing sophisticated analytics infrastructure. Malaysian SME research by Nordin et al. (2025),

although focused on digital advertising rather than inventory, similarly highlights the value of explicitly structured, interpretable decision-evaluation components. Accordingly, the contextual contribution is to examine the practical applicability and boundary of this decision-level OIPT specification among purposively recruited Selangor SME respondents, not to claim national representativeness or distinctive Malaysian effects. Using cross-sectional survey evidence from 360 respondents, the study addresses the following research questions:

RQ1: To what extent are information quality and analytical capability associated with decision information use in SME inventory replenishment?

RQ2: Is decision information use associated with perceived replenishment decision effectiveness after accounting for information quality and analytical capability?

RQ3: Are information quality and analytical capability indirectly associated with perceived replenishment decision effectiveness through decision information use when their direct associations are retained in the model?

Theory and hypothesis development

Information-processing logic

Organisational Information Processing Theory (OIPT) argues that organisations should match information-processing arrangements to the demands created by task uncertainty (Galbraith, 1974). In supply chains, uncertainty can originate in forecast variation, supplier lead times and the relationship between physical stock and recorded inventory (Chen et al., 2000; DeHoratius & Raman, 2008). The model therefore distinguishes three analytically separate stages: the quality of decision inputs, the capability to analyse those inputs, and their incorporation into a replenishment choice. This interpretation is consistent with Cao et al.'s (2015) organisational information-processing mechanism and with Jonsson and Myrelid's (2016) decision-process account of information utilisation. Neither theoretical approach, however, establishes that the specified inventory-level sequence is causal when assessed with contemporaneous self-reports (Maxwell & Cole, 2007).

Information quality and decision information use

Information quality (IQ) is conceptualised as the perceived accuracy, completeness, relevance and timeliness of data available for a replenishment decision. Wang and Strong (1996) show why data quality must be assessed from the information consumer's task context, rather than by accuracy alone. DeLone and McLean (2003) distinguish information quality from system use within information-systems success, and Li and Lin (2006) examine information quality separately from information sharing in supply-chain relationships. At a more decision-specific level, Jonsson and Myrelid (2016) identify information quality and intended usage as antecedents to actual supply-chain information utilisation. Although Lem (2024) connects analytics strategy with internal information quality, that study does not test information use in SME inventory ordering. These distinctions justify the following expectation without presuming its empirical truth. H1: Information quality is positively associated with decision information use.

Analytical capability and decision information use

Analytical capability (AC) refers here to personnel's perceived ability to interpret inventory records, compare demand patterns and assess ordering alternatives. Cao et al. (2015) show that business analytics can contribute to decision-making effectiveness through information-

processing arrangements, whereas Chen et al. (2022) examine big-data analytics capability in relation to strategic decision speed and quality. Raj et al. (2025) provide meta-analytic evidence about analytics capability, supply-chain capabilities and operational performance, but their mediating constructs are broader than the information-use behaviour proposed here. Jonsson and Myrelid (2016) likewise suggest that available information is not automatically integrated into planning processes. The hypothesised link is therefore between the capability to interpret information and the reported use of that information in a specified operational decision. H2: Analytical capability is positively associated with decision information use.

Information use, effectiveness and indirect associations

Decision information use (DIU) concerns respondents' reported reliance on relevant records while assessing replenishment quantities and timing; perceived replenishment decision effectiveness (RDE) captures their assessment of whether those decisions were appropriate and timely. Use and outcomes should remain conceptually distinct: DeLone and McLean (2003) separate information-system use from success outcomes, while Jonsson and Myrelid (2016) distinguish the actual use of shared supply-chain information from its mere availability. Cao et al. (2015) report an information-processing route to organisational decision effectiveness, and Abdellatif et al. (2024) find mediation through decision speed and comprehensiveness; neither study establishes the particular DIU-to-RDE mechanism. H3: DIU is positively associated with RDE after accounting for IQ and AC. H4a: DIU carries a positive statistical indirect association between IQ and RDE. H4b: DIU carries a positive statistical indirect association between AC and RDE. Because a cross-sectional indirect effect is not equivalent to a longitudinal causal mechanism, these hypotheses are explicitly associational (Maxwell & Cole, 2007).

Figure 1 presents the proposed partial-mediation framework, in which information quality and analytical capability relate to replenishment decision effectiveness both directly and through decision information use. The reported standardised path estimates are also displayed.

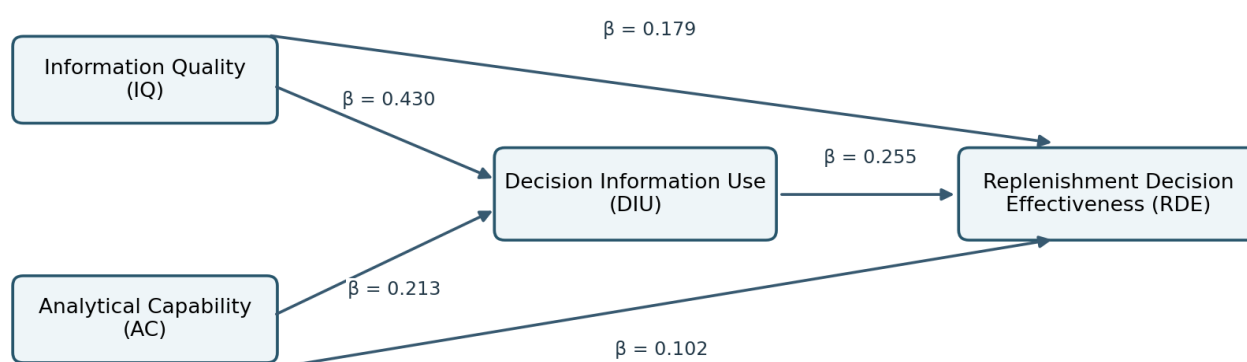


Figure 1. Proposed partial-mediation framework and composite-score path estimates.

Construct distinctiveness and rival mechanisms

The constructs identify different properties of an information-to-decision process. IQ refers to qualities of the data, AC to the abilities and routines used to interpret them, and DIU to the reported incorporation of information into a choice. This distinction is grounded in data-quality research (Wang & Strong, 1996), information-systems success research (DeLone &

McLean, 2003), and the supply-chain information-utilisation model of Jonsson and Myrelid (2016). An SME may keep accurate stock records without consulting them before an order, or possess analytical skills without timely access to usable inventory data. Accordingly, broad analytics-performance associations (Raj et al., 2025) cannot by themselves validate a decision-specific mediator.

There are plausible rival accounts. Firms with mature replenishment routines may invest in both high-quality information and analytical practices, producing common causes of reported use and effectiveness. Managers who recall successful orders may retrospectively rate the information and decision process more favourably. Because the measures are contemporaneous respondent reports, common-method effects are also possible (Podsakoff et al., 2003). More fundamentally, cross-sectional mediation models can distort the magnitude and direction of longitudinal indirect effects (Maxwell & Cole, 2007). The fitted model estimates conditional statistical associations but cannot eliminate these rival explanations.

The proposed contribution is narrower than an overarching analytics-capability explanation of supply-chain outcomes. Raj et al. (2025) synthesise relationships among analytics, integration, flexibility, resilience and operational performance, whereas Jonsson and Myrelid (2016) analyse stages of actual information utilisation in supply-chain planning. The present study brings these connected literatures to a specific SME replenishment choice by estimating associations among information quality, analytical capability, decision information use and perceived decision effectiveness. The argument is one of operational specificity, not a claim to have discovered information utilisation as a new concept.

Methods

Design, provenance and measurement

The study examined inventory replenishment decision-making among small and medium-sized enterprises (SMEs) in Selangor, Malaysia. Data collection took place in October 2026, and purposive sampling was used to recruit respondents relevant to SME inventory replenishment. The study comprised 360 survey responses. Because purposive sampling is a non-probability approach, the sample should be understood as analytically relevant to the study setting rather than statistically representative of all SMEs in Malaysia. The unit of analysis was the individual survey response, and the outcome captures perceived replenishment decision effectiveness.

Four constructs were analysed: information quality (IQ), analytical capability (AC), decision information use (DIU), and perceived replenishment decision effectiveness (RDE). The analysis used four five-point survey items per construct, with an unweighted item average representing each composite. Their interpretation is theoretically informed by the distinction between data-quality dimensions (Wang & Strong, 1996), supply-chain information utilisation (Jonsson & Myrelid, 2016), and analytics-related decision capabilities (Cao et al., 2015; Raj et al., 2025). These publications provide conceptual grounding; the study does not claim that its exact questionnaire items were adopted from those sources. The outcome reflects respondents' assessments of replenishment decisions rather than independently observed stockout or inventory-cost outcomes.

Model specification and inference

The survey responses were analysed using IBM SPSS Statistics. The specified composite-score mediation model comprised two ordinary least squares equations: $DIU = \alpha_0 + a_1IQ + a_2AC + \varepsilon_1$; and $RDE = \beta_0 + bDIU + c'_1IQ + c'_2AC + \varepsilon_2$. By retaining both direct paths in the outcome equation, the specification distinguishes a_1b and a_2b as specific indirect associations from c'_1 and c'_2 as conditional direct associations. The previously reported estimates are standardised coefficients, with 95% percentile bootstrap intervals based on 2,500 resamples. Percentile intervals are a recognised inferential choice for indirect-effect analysis, although alternative methods have different statistical properties (Hayes & Scharkow, 2013). These are OLS composite-score results, not latent-variable PLS-SEM output.

This cross-sectional design supports conditional association statements, not causal interpretations or claims about the temporal ordering of the mediator and outcome (Maxwell & Cole, 2007). Bootstrap resampling quantifies model-based sampling uncertainty but does not remove confounding, selection effects or common-source reporting biases (Podsakoff et al., 2003). Hence the results are interpreted as associations among reported constructs for purposively recruited respondents.

Analytical safeguards and reproducibility

The unit of analysis was an individual survey response rather than an independently logged replenishment transaction. Both predictors entered the mediator equation simultaneously; DIU and both predictors entered the effectiveness equation. Direct paths were retained to avoid treating mediation as complete by model specification alone. This follows the distinction between a statistically estimable indirect effect and a causally identified mediation process emphasised in methodological work (Maxwell & Cole, 2007; Hayes & Scharkow, 2013).

Descriptive statistics and Pearson correlations summarised the four composite measures. Cronbach's alpha was reported as an indicator of internal consistency. Standardised OLS path coefficients, model R^2 values, and percentile bootstrap intervals summarised the specified mediation model. As an additional descriptive assessment of model sensitivity, alternative rank-transformed composites and three-item composites were compared with the principal four-item specification. These checks address sensitivity to specification choices, not external predictive validity.

Cronbach's alpha was used for descriptive reliability screening, not as a stand-alone test of construct validity or dimensionality. As Sijtsma (2009) demonstrates, alpha by itself does not establish the underlying internal structure of a scale. Likewise, positive cross-sectional indirect effects are not sufficient evidence of causal mediation (Maxwell & Cole, 2007).

Results

Table 1 summarises the means, standard deviations and observed ranges of the four composite measures used in the regression analyses.

Table 1

Composite descriptive statistics

Construct	Mean	SD	Observed range
IQ	3.088	0.735	1.00–5.00
AC	3.028	0.740	1.00–4.75
DIU	3.075	0.756	1.25–5.00
RDE	3.071	0.720	1.00–5.00

Source: Authors' analysis of SME survey responses (n = 360).

Table 2 presents Pearson correlations among the four constructs, providing an initial view of their bivariate associations before regression analysis.

Table 2

Pearson correlations of composite scores

	IQ	AC	DIU	RDE
IQ	1.000	0.100	0.451	0.304
AC	0.100	1.000	0.257	0.185
DIU	0.451	0.257	1.000	0.362
RDE	0.304	0.185	0.362	1.000

Source: Authors' analysis of SME survey responses (n = 360).

Cronbach's alpha was used to assess internal consistency for each four-item scale; the estimates reported in Table 3 range from 0.806 to 0.841.

Table 3

Reliability screening

Construct	Items	Cronbach α
IQ	4	0.841
AC	4	0.812
DIU	4	0.825
RDE	4	0.806

Source: Authors' analysis of SME survey responses (n = 360).

Table 4 reports standardised direct-path estimates from the mediator and outcome regressions, together with bootstrap standard errors and 95% percentile confidence intervals.

Table 4

Direct associations (standardised composite-score OLS)

Path	β	Boot. SE	95% percentile CI
IQ $\rightarrow$ DIU	0.430	0.043	[0.348, 0.513]
AC $\rightarrow$ DIU	0.213	0.047	[0.121, 0.304]
DIU $\rightarrow$ RDE IQ, AC	0.255	0.056	[0.150, 0.368]
IQ $\rightarrow$ RDE DIU, AC	0.179	0.053	[0.075, 0.283]
AC $\rightarrow$ RDE DIU, IQ	0.102	0.050	[0.005, 0.200]

Source: Authors' analysis of SME survey responses (n = 360).

The mediator model explained 24.9% of DIU variation ($R^2 = 0.249$); the outcome model explained 16.5% of RDE variation ($R^2 = 0.165$). These values describe explained variance in the self-reported composite scores, not objectively observed inventory performance.

Table 5 presents the specific indirect associations through information use, the corresponding total associations, and their 95% percentile bootstrap confidence intervals.

Table 5

Specific indirect and total associations

Path	Estimate	95% percentile CI
IQ → DIU → RDE	0.110	[0.062, 0.170]
AC → DIU → RDE	0.054	[0.026, 0.093]
IQ total association	0.288	[0.194, 0.385]
AC total association	0.156	[0.059, 0.253]

Source: Authors' analysis of SME survey responses (n = 360).

Figure 2 visualises the two reported indirect associations with their 95% percentile bootstrap confidence intervals, both of which exclude zero.

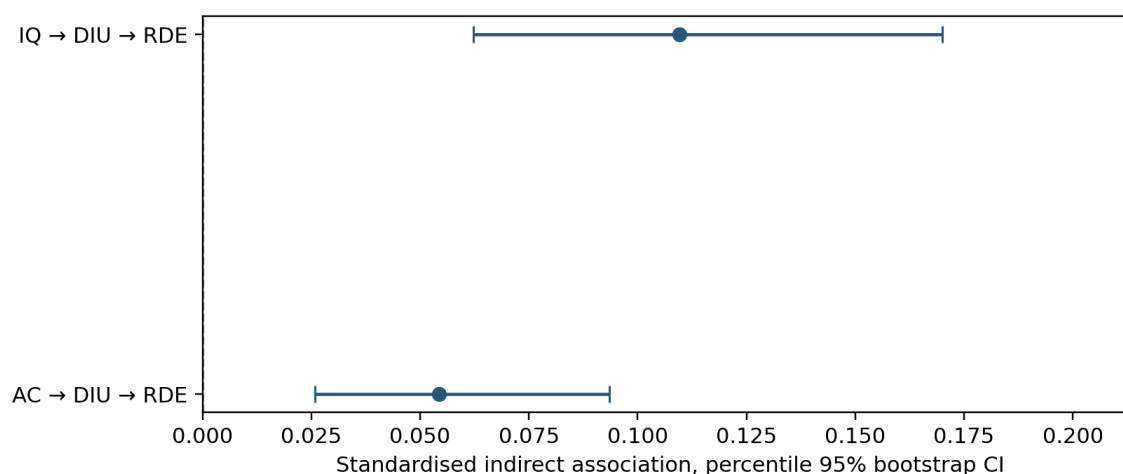


Figure 2. Indirect effects with percentile bootstrap confidence intervals.

Sensitivity analyses

Table 6 compares the primary four-item composite model with rank-transformed composites and a three-item specification to assess the stability of the reported paths.

Table 6

Descriptive robustness checks under alternative composite specifications

Specification	IQ → DIU	AC → DIU	DIU → RDE	IQ → RDE	AC → RDE
Primary: 4-item average	0.430	0.213	0.255	0.179	0.102
Rank-transformed composite	0.421	0.219	0.229	0.204	0.125
First three items per construct	0.388	0.207	0.246	0.172	0.102

Source: Authors' analysis of SME survey responses (n = 360).

The signs of the focal paths remained positive in both sensitivity specifications. These tests gauge sensitivity to a rank transformation and exclusion of the fourth indicator from each construct; they do not substitute for independent measurement validation, causal identification, or external prediction tests. The last specification is a sensitivity calculation, not a recommendation to delete items.

Discussion

The reported estimates indicate positive associations between both information quality and analytical capability and decision information use, followed by a positive conditional association between DIU and perceived replenishment effectiveness. The indirect associations remain positive when direct paths are included, consistent with a partial-mediation representation in the statistical sense. These findings fit the general distinction between data quality and use advanced by DeLone and McLean (2003) and the information-utilisation sequence described by Jonsson and Myrelid (2016). However, the RDE model explains 16.5% of its composite-score variation, and the fitted paths do not demonstrate that increasing information use would cause objective inventory improvements (Maxwell & Cole, 2007).

Theoretical implications and competing explanations

The findings are positioned alongside, rather than above, existing theory. Cao et al. (2015) demonstrate an organisational-level relationship between analytics, information processing and decision effectiveness; Lem (2024) examines analytics strategy and internal information quality. Chen et al. (2022) focus on strategic decision-making under disruption, and Abdellatif et al. (2024) examine decision speed and comprehensiveness, not the present DIU construct. Jonsson and Myrelid (2016) provide an especially close conceptual precedent by tracing the utilisation of information in supply-chain planning. The present paper's more limited contribution is to examine a specific SME replenishment-decision pathway linking IQ, AC, DIU and perceived RDE; it is not evidence that information utilisation or mediation was previously absent from operations research.

Alternative mechanisms remain compatible with the coefficient pattern. More mature operations may support stronger information practices and more favourable self-ratings; perceived success may affect retrospective reports of information use; and same-source questionnaires can generate common-method variance (Podsakoff et al., 2003). Multi-wave research would be preferable for separating hypothesised mediation from reverse attribution, and objectively recorded orders would help distinguish perceived from actual effectiveness (Maxwell & Cole, 2007; DeHoratius & Raman, 2008).

Table 7 summarises rival interpretations of the reported associations and identifies additional evidence needed to differentiate these explanations in future research.

Table 7

Rival explanations and proposed empirical tests

Rival explanation	Why the present design cannot eliminate it	Needed field evidence
Organisational maturity	Capabilities, use and outcomes may share an omitted cause	Firm maturity, process controls and multi-respondent records
Reverse attribution	Perceived success may shape retrospective use reports	Prospective information-access logs before orders
Common method bias	All constructs share a single survey mode	Inventory records, supervisor ratings and timestamped decisions
Contextual uncertainty	Demand shocks and supplier variability are uncontrolled	Lead-time variability, SKU-level demand and sector controls

Source: authors' conceptual synthesis of potential rival explanations and proposed empirical tests.

Contribution relative to adjacent literature

The substantive contribution is to examine established information-processing ideas at the level of SME replenishment decisions, separating information quality, analytical capability and information use rather than treating them as a single undifferentiated digital capability (Galbraith, 1974; Cao et al., 2015; Jonsson & Myrelid, 2016). The Malaysian SME contextualisation is consistent with Nordin et al.'s (2025) observation, in the different domain of digital advertising, that interpretable evaluation components can matter for smaller businesses' management decisions. This parallel concerns structured decision support, not a demonstrated transfer of marketing findings to inventory operations. The relatively limited explanatory power also suggests a role for omitted operational and organisational conditions.

The relationship to prior research should not be overstated. Lem (2024) assesses internal information quality associated with analytics strategy; Abdellatif et al. (2024) identify speed and comprehensiveness as intermediate decision facets; and Raj et al. (2025) synthesise supply-chain capability mechanisms at a broader level. By contrast, the focal mediator in this paper is reported use of information when deciding on inventory replenishment. This narrower behavioural definition is consistent with the utilisation concerns raised by Jonsson and Myrelid (2016), though the present outcome is perceptual rather than transaction-based.

An outcome-model R^2 of 0.165 indicates that most variation in perceived replenishment effectiveness is not captured by the three included explanatory variables. Inventory-replenishment performance depends on several other plausible influences, including demand forecasting and lead-time information (Chen et al., 2000), physical-stock record accuracy and auditing (DeHoratius & Raman, 2008), and the reliability of supply-chain information exchange (Li & Lin, 2006). Supplier arrangements, available financing, order approval routines and product assortment may also affect decisions, but were not separately estimated in the current model. These are candidates for future specification rather than mechanisms established by this analysis.

Practical implications

The practical interpretation is diagnostic rather than prescriptive. SME managers can distinguish (i) whether inventory and supplier records are sufficiently accurate and decision-relevant, (ii) whether staff can compare replenishment alternatives and (iii) whether evidence was actually used to determine order quantities and timing. Concerns about record inaccuracy are supported by DeHoratius and Raman (2008), while the need to distinguish shared information from actual utilisation is consistent with Jonsson and Myrelid (2016). A lightweight decision log might record stock positions, demand estimates, data sources consulted, reorder thresholds, approved quantities and later stock outcomes. Such a log is a proposed evaluation tool, not an intervention whose effectiveness has been established by this cross-sectional study.

Scope and boundaries

The results concern self-reported composite scores, not independently verified order fulfilment, stockout reductions, inventory cost savings or treatment effects. Cross-sectional regression-based indirect effects should not be interpreted as identified causal pathways (Maxwell & Cole, 2007), and common-source measurement introduces potential response bias (Podsakoff et al., 2003). The findings therefore inform a more focused decision-process account rather than a claim of proven inventory-performance improvement.

Decision-level implementation and testable managerial actions

A defensible implementation sequence would begin with a small audit of actual replenishment episodes, not necessarily with the purchase of another digital platform. For each order, a firm could document physical and recorded stock, expected demand, supplier delivery estimates, decision alternatives, evidence consulted, approval time and eventual inventory consequences. Research on inventory-record inaccuracies illustrates why reconciliation may be an important prerequisite (DeHoratius & Raman, 2008); research on supply-chain information utilisation illustrates why merely transmitting information does not guarantee its use in planning (Jonsson & Myrelid, 2016).

These records would help compare targeted interventions: data reconciliation for unreliable stock balances, analytical training for difficulties in comparing order alternatives, and decision checklists for failures to consult otherwise available evidence. Such options should be evaluated against observed errors and costs, not selected by ranking standardised cross-sectional regression coefficients. The proposed distinction between input quality, processing capabilities and actual use follows Galbraith (1974), Wang and Strong (1996), and Jonsson and Myrelid (2016).

Future research could prospectively link survey respondents to actual replenishment episodes, measure decision latency and stockouts, and account for business size, demand variability, supplier lead times and product mix. Repeated observations and independently recorded operational outcomes would more directly address the temporal and reporting limitations identified by Maxwell and Cole (2007) and Podsakoff et al. (2003).

Limitations and future research

Three limitations are important. First, purposive sampling does not justify probabilistic generalisation from the respondent group to all Malaysian SMEs. Second, contemporaneous,

same-source measures may be affected by common-method bias and cannot establish time-ordered mediation (Podsakoff et al., 2003; Maxwell & Cole, 2007). Third, the dependent construct represents perceived rather than independently verified replenishment effectiveness, and Cronbach's alpha alone does not establish unidimensionality or construct validity (Sijtsma, 2009). Future work should validate the instrument more extensively, collect multi-source evidence, and associate information-use behaviours with SKU-level stockouts, costs and replenishment lead times.

Conclusion

This study examined information quality, analytical capability, decision information use and perceived replenishment decision effectiveness in a reported sample of 360 SME survey respondents in Selangor, Malaysia. Both information quality and analytical capability showed positive associations with decision information use, and use was positively associated with perceived replenishment effectiveness after accounting for both predictors. Positive specific indirect associations were reported while retaining direct paths. Consistent with information-processing and utilisation theory (Galbraith, 1974; Jonsson & Myrelid, 2016), the findings support considering information resources, analytical capabilities and their reported application as distinct dimensions of operational decision-making. The study's conclusions are associational; prospective research using validated instruments and observed inventory decisions is needed to test causal and operational effects.

References

- Abdellatif, M. A. M., Abubakar, A. M., Elayan, M. B. H., & Hayajneh, J. A. M. (2024). Business analytics capabilities and decision quality: The mediating roles of decision speed and comprehensiveness. *Information Systems Management*, 41(1), 91–108. <https://doi.org/10.1080/10580530.2023.2179704>
- Cao, G., Duan, Y., & Li, G. (2015). Linking business analytics to decision making effectiveness: A path model analysis. *IEEE Transactions on Engineering Management*, 62(3), 384–395. <https://doi.org/10.1109/TEM.2015.2441875>
- Chen, F., Drezner, Z., Ryan, J. K., & Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. *Management Science*, 46(3), 436–443. <https://doi.org/10.1287/mnsc.46.3.436.12069>
- Chen, L., Liu, H., Zhou, Z., Chen, M., & Chen, Y. (2022). IT-business alignment, big data analytics capability, and strategic decision-making: Moderating roles of event criticality and disruption of COVID-19. *Decision Support Systems*, 161, 113745. <https://doi.org/10.1016/j.dss.2022.113745>
- DeHoratius, N., & Raman, A. (2008). Inventory record inaccuracy: An empirical analysis. *Management Science*, 54(4), 627–641. <https://doi.org/10.1287/mnsc.1070.0789>
- DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, 19(4), 9–30. <https://doi.org/10.1080/07421222.2003.11045748>
- Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28–36. <https://doi.org/10.1287/inte.4.3.28>
- Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? *Psychological Science*, 24(10), 1918–1927. <https://doi.org/10.1177/0956797613480187>

- Jonsson, P., & Myrelid, P. (2016). Supply chain information utilisation: Conceptualisation and antecedents. *International Journal of Operations & Production Management*, 36(12), 1769–1799. <https://doi.org/10.1108/IJOPM-11-2014-0554>
- Lem, K. W. (2024). Data analytics strategy and internal information quality. *Contemporary Accounting Research*, 41(2), 1376–1410. <https://doi.org/10.1111/1911-3846.12942>
- Li, S., & Lin, B. (2006). Accessing information sharing and information quality in supply chain management. *Decision Support Systems*, 42(3), 1641–1656. <https://doi.org/10.1016/j.dss.2006.02.011>
- Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, 12(1), 23–44. <https://doi.org/10.1037/1082-989X.12.1.23>
- Nordin, M. S., Che Hussin, A. R., & Mohamad Zaid, A. A. (2025). Key components for evaluating paid digital advertising (PDA) performance for SMEs in Malaysia. *International Journal of Academic Research in Business and Social Sciences*, 15(12), 1806–1813. <https://doi.org/10.6007/IJARBSS/v15-i12/27302>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Raj, A., Kumar, R. R., Narayanan, S., Kirca, A. H., & Jeyaraj, A. (2025). Analytics capability, supply chain capabilities, and operational performance: A meta-analytic investigation. *Journal of Operations Management*, 71(6), 786–805. <https://doi.org/10.1002/joom.1376>
- Sijtsma, K. (2009). On the use, the misuse, and the very limited usefulness of Cronbach's alpha. *Psychometrika*, 74(1), 107–120. <https://doi.org/10.1007/s11336-008-9101-0>
- Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, 12(4), 5–33. <https://doi.org/10.1080/07421222.1996.11518099>